Active Inference and Psychology of Goals: A study in Substance and Process Metaphysics

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Abstract

Active Inference and its accompanying Bayesian Mechanics (BM) are important psychological and cognitive science theories. While there is a strong interaction between the theories and the philosophical realm, it needs to be clarified what its metaphysical commitments are. We tease out these commitments while looking from the perspective of the psychology of goals. We find that Active Inference cannot account for the dynamic growth of goals, primarily because of its closed generative model. We trace the reason for this through the extrinsic 'ontological constraint' of BM, characteristic of all mechanistic models which follow the 'logic of machines.' Finally, we ground our arguments in the necessity of external relations in substance metaphysics and its incompatibility with internal relations and impredicativity. Thus we argue that Active Inference implicitly presupposes a Substance metaphysics, yielding the theory no resource to model novelty, growth, and development observed in human psychology. We briefly sketch a powerful alternative grounded in process metaphysics to model biological and cognitive systems.

Keywords: Active Inference; Goals; Generative Models; Metaphysics; Impredicativity; Internal Relations

Introduction

Friedrich von Weizsäcker famously said, 'Every scientist works with metaphysical assumptions, and those who deny this most usually work with the poorest ones.' As a discipline, Cognitive Science is one of the few sciences explicitly acknowledging philosophy as a core part of itself. However, even in Cognitive Science, facets of philosophy other than the philosophy of mind are seldom considered – like ontology and metaphysics. We intend to undertake a study that points to the value of metaphysics – especially process metaphysics – and analyze implicit assumptions in one of psychology's core theories, Active Inference.

Active Inference has been central in cognitive science and psychology for almost two decades. It is also one of the few psychological theories that engage critically with the philosophy of mind (mental representations) and philosophy of science (realist and instrumentalist reading of Active Inference). However, to date, it has yet to be clear what the metaphysical commitments of the theory are, and not much elaboration has been offered. We make one such attempt in this study. Notably, we focus on the goal-oriented aspect of human psychology to highlight and illuminate these commitments.

By psychology of goals, we do not mean anything fancy other than the activities of everyday life - like the goal to finish a paper, which suddenly changes to cooking a meal, switching to paying utility bills, or maybe transitioning to completely disparate goals. Our focus is on this dynamicity, flexibility, and fluidity with which goals change, emerge, and develop over ontogenetic time. More importantly, change and emergence from within the system, i.e., internal & intrinsic goals, and not imposed by an external experimenter - as in the case of laboratory bandit tasks. Our primary thesis is that Active Inference, as it is currently formulated, cannot account for this dynamicity of goal-oriented activities.

Active Inference is the idea that humans perceive and act on the world through Bayesian Inference (perception as inference, planning as inference) via variational free energy minimization (VFEM) (Parr, Pezzulo, & Friston, 2022). While the perception as inference is a crucial part of the story, we will focus here on the action part and the associated goals it achieves. The system's goals are baked into the priors of the generative model that the system embodies (Ramstead, Friston, & Hipólito, 2020). Thus, goals are instantiated through priors on observations (in discrete-time Active Inference, called C-matrix) that the system wants to observe. This goal-informed prior forces the system to infer actions that yield the said goals.

In many ways, this is a generalized form of model-based reinforcement learning. Instead of a separate reward function, goals are cast as a probabilistic belief on sensory observations yielding one inference scheme for both action and perception (Millidge, Tschantz, & Buckley, 2021). There are other properties like learning and uncertainty handling, but these are not of concern for our inquiry.

The crucial point to note here is that irrespective of which time-setting (discrete or continuous) one is working with Active Inference, the generative model and its associated goals are always 'closed.' By 'closed,' we mean the inability to change, grow, and evolve by itself. In short, a closed set of goals is embodied through priors on a fixed set of observations. A fixed, a-priori-specified set of actions is used to achieve these goals.

This closed-ness of Active Inference comes from the 'high road to Active Inference,' (Parr et al., 2022) or what is recently called Bayesian Mechanics (Ramstead et al., 2022). We want to draw attention to the critical assumption in this 'high road': if a 'thing' exists, then there is a stipulated definition of 'the kind of thing that it is' (Ramstead et al., 2022).

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This 'thingness' is also called the 'ontological potential or constraint' of the thing.

> 'Ontological potentials or constraints provide a mathematical definition of what it means for a particular system to be the kind of system that it is: they allow us to specify the equations of motion of particular systems, based on description of what sorts of states or paths are *typical* of that kind of system' (Ramstead et al. (2022), emphasis ours).

These 'typical states' are also called phenotypic states (in the case of biological systems) of the 'thing' (Ramstead, Kirchhoff, & Friston, 2020). The question then becomes where these phenotypic states come from and what is its nature. The acknowledged answer in Active Inference literature is that they are evolution-endowed innate characteristics (Friston, Kilner, & Harrison, 2006).

The critical point here is that these 'ontological constraints' are not *intrinsic* to the system's dynamics but are rather *extrinsic*. I.e., they influence the system's dynamics but are not themselves influenced by the dynamics. This inability to model *intrinsic* constraints is traced to a logical necessity inherent in Bayesian Mechanics (and all mechanics), which Koutroufinis (2017) calls 'logic of machines.' We further argue that this logic is a natural outcome of substance metaphysical assumptions, thereby showing us where Active Inference is metaphysically grounded.

Several authors have raised issues about other aspects of Bayesian Mechanics and Active Inference, like lack of historicity (Paolo, Thompson, & Beer, 2022), fixed state-space (Colombo & Wright, 2021), and inability to capture constitutive relations (Raja, Valluri, Baggs, Chemero, & Anderson, 2021). These problems' root is an implicit substance metaphysical assumption in Bayesian mechanics. This assumption gets cashed out in Active Inference as a closed generative model with a fixed set of priors – 'priors that correspond to innate value and are part of the (generative) model per se' (Friston et al., 2006).

In what follows, we elaborate on why we think Active Inference, as it is currently formalized, cannot account for novelty and development in the psychology of goals. The fundamental thesis is that it presupposes a substance ontology through its 'logic of machines' in Bayesian mechanics - An ontology that makes any form of *internal relations* and *impredicative* causality impossible and thus any real change, growth & development.

Furthermore, we elaborate on the necessity of process metaphysics to account for impredicativity & internal relations within our scientific models. We briefly sketch Robert Rosen's relational modeling and argue how its tools to model complex systems are a strong candidate to explain the dynamicity of biological and cognitive systems. We end the study with some concluding remarks.

Active Inference and Substance Metaphysics

The theory of Active Inference has two routes of entry, the low road and the high road to Active Inference (Parr et al., 2022). For psychological modeling, most Active Inference researchers use the tools of the low road to model perception, action, and learning. The high road justifies those tools from ontological first principles – like free energy minimization rather than MCMC sampling for Bayesian inference. To that extent, we will introduce the basic concepts of the low road before making contact with the high road, also called Bayesian Mechanics (BM) (Costa, Friston, Heins, & Pavliotis, 2021; Ramstead et al., 2022).

The low road starts with the assumption that human perception is a kind of inference, continuing in the Helmholtzian idea of 'unconscious inference' (Buckley, Kim, McGregor, & Seth, 2017). Why inference? Well, the argument is that sensory data hitting the retina is substantially reduced compared to the rich three-dimensional world that we perceive.[1] So, the brain has to infer the outside world (hidden state, s) by combining the sensory data (observation, o) with prior knowledge (generative model, $p(o,s)$) to re-present the world in our perception ($p(s|o)$).

The standard cognitivist theory in psychology posits that this re-presentation undergoes further mental processing to plan optimal actions based on a separate utility/reward function. This view is the case in most decision-making theories like model-based Reinforcement learning. However, the major innovation in Active Inference is unifying perception and action under one inference scheme by instituting a perception-action loop (Millidge et al., 2021).

The idea is that the agent *expects* to observe certain sensory data and acts to bring about those observations – 'given the assumption that I will achieve my preferred outcomes, what course of action am I most likely to pursue?' (Smith, Friston, & Whyte, 2022; Millidge et al., 2021). Thus, given certain preferred future observations (goals, called C-matrix in discrete Active Inference), the system infers which plan (sequence/course of action) would bring those observations. This inference is called 'planning as inference' (Smith et al., 2022). Once a particular observation is generated, the system compares it with its *expected* observation to perceptually infer the world. This 'perception as inference' then feeds into changing the course of action (if needed), thus completing the perception-action loop.

One optimal way to do all this is through Bayesian inference. Since Bayesian inference is intractable for most real-world complexity, variational free energy minimization (VFEM) is introduced as an approximate Bayes-optimal solution[2]. The key player in this inference scheme is the generative model, instantiating the prior knowledge of the system.

[1] For a rejection of this 'poverty of the stimulus' argument, see (Bickhard & Richie, 1983)

[2] See Kwisthout and van Rooij (2020); Kwisthout, Wareham, and Rooij (2011) for a rebuttal to tractability of approximation algorithms

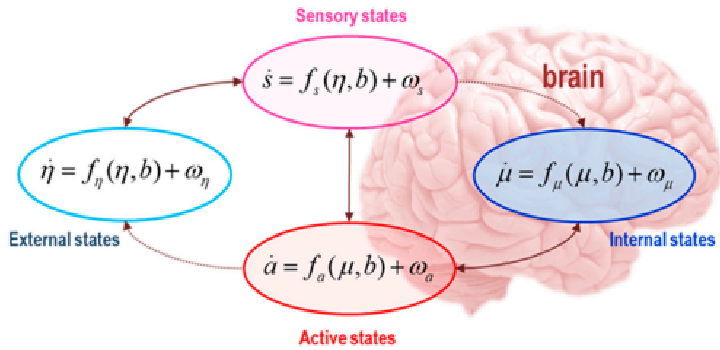

Figure 1: An agent-environment system particularly partitioned by its Markov Blanket. The Active and Internal states constitute the Autonomous states of the system while adding Sensory states to them constitutes the particle - also called Particular states. (Figure from Friston et al. (2021); used under CREATIVE COMMON ATTRIBUTION LICENSE)

The generative model specifies which observations the system prefers (goals), how actions change the outside world (state transition, B-matrix), which hidden state yields which observations (likelihood function, A-matrix), etc. It is fair to say that almost everything (except VFEM) in Active Inference comes down to the prior knowledge and prior preferences instantiated in the generative model.

Given this introduction, we are now in an excellent position to ask whether the theory of Active Inference can explain dynamic, emergent goals. One way of viewing the question in light of previous paragraphs is, can the generative model dynamically grow w.r.t its goals? Unfortunately, we do not think it can. The generative models are closed, allowing only a finite and fixed set of goals embodied as a prior on a finite set of observations.

Several authors have previously noted this shortcoming of closed generative models in Active Inference. For example, in the context of learning, 'we would be missing a means of representing all the new categories that are constantly being developed' like 'neutrino, blockchain, tweet, and bitcoin' (Rutar, de Wolff, van Rooij, & Kwisthout, 2022) and in the context of expectations, 'This introduction of a novel category/concept was a puzzle ... and realized that the fixed state space of a dynamical POMDP (like the one used here) currently lacks the flexibility to model such emergent expectations' (Raghuveer & Endres, 2023) - highlighting the limitations of closed models. In the upcoming sections, we will identify and point out the root of such limitations.

Bayesian Mechanics

To analyze the finite and closed characteristics of generative models and goals, we must turn to Bayesian Mechanics – the high road to Active Inference (Parr et al., 2022; Ramstead et al., 2022). As noted earlier, Bayesian Mechanics (BM from here on) furnishes justification for using tools like VFEM, action-perception loop, and prior expectations from ontological first principles.

Notably, it starts with the question of what it means for a thing to exist. Quoting Friston et al. (2022):

- 'If something exists, in the sense of possessing characteristic states or dynamics, what properties must it possess? To answer this question, it is necessary to define a thing or particle.'
- 'A particle is constituted by internal and blanket states. The blanket states constitute the boundary between the states internal and external to the particle.'

We do not have to concern ourselves with the boundary or 'particular partition' for now, but let us focus on the first step. The foundational assumption in BM is that every system that exists is described by a stochastic dynamical system of the form:

$$\dot{x}(t) = f(x_t) + \omega(t) \tag{1}$$

Where $f(x_t)$ is the deterministic flow and $\omega(t)$ is the stochastic noise. Once this is assumed, the next move is partitioning the system into internal, sensory, active, and external states (Figure 1). This partition is formalized by partitioning the dynamical system into four components - f_μ, f_s, f_a, f_η and their corresponding noise terms. As quoted in Friston et al. (2022) above, the 'thing' is then constituted by internal and blanket states.

Since BM is affirmed as a theory of self-organizing systems, it assumes that there is a set of 'characteristic' states/dynamics that the system self-organizes into. These states/paths define the 'thing' as 'the kind of thing it is' (Ramstead et al., 2022). They are called 'ontological constraints' of the 'thing.'

Given this set of characteristic states, one can describe the system's dynamics as a random dynamical system with a pullback attractor. These dynamics could be given a probabilistic description using the Fokker-Planck equation, yielding the generative model ($p(x)$) with its attractor states as prior *expectations* of the system. That is a probability distribution on states that encodes a high probability for attractor states than other states.

The innovation in BM is the particular assumption on the nature of 'partition' (Markov Blanket) within the system. The conditional independence following this assumption leads to interesting results - like autonomous states look *as if* they are minimizing surprisal w.r.t external states - yielding the VFEM scheme and perception-action loop. However, our focus is not that per se, but rather on the nature and origin of the goals instantiated as prior *expectations* of the 'thing.' Let us first start with the origin.

Given the above elucidation, it is easy to see that the goals of a system are intricately linked to its 'characteristic states' – the states a system *expects* to be in. In fact, Ramstead et al. (2022) explicitly states that 'we can think of this [attractor] solution to the dynamics as a naturalised account of the *teleology* of cognitive systems' (emphasis ours). For a biological system, the characteristic states are also called phenotypic states of the system –

> 'organisms expect to be in their characteristic phenotypic states; surprising deviations from these *expectations* must be avoided to maintain the system within viable (i.e., phenotypic) states' (Ramstead, Kirchhoff, and Friston (2020), emphasis ours).

So where do phenotypic states come from? The well-acknowledged answer to this question in the literature is that they are innate, originating from evolution (Friston, Samothrakis, & Montague, 2012; Friston et al., 2006; Friston, 2010; Badcock, Friston, Ramstead, Ploeger, & Hohwy, 2019). This is the crucial part. The characteristic phenotypic states are imposed through evolution and are not produced through the dynamics or current activity of the system itself.

To reiterate, the 'characteristic states' of the system, acquired through ancestral evolution, determine the 'ontological constraint,' which directs the system's deterministic flow, $f(x)$. The influence flow is one-way, i.e., the characteristic states and ontological constraints influence the system's dynamics but not vice versa. The asymmetry between the system's dynamics and 'ontological constraints' makes those constraints *external* (in origin) and *extrinsic* (in nature). With these answers to our question of the origin and nature of goals, we will now move on to their implications.

Intrinsic and Extrinsic Constraints

The next question is, why can't the 'ontological constraints' be influenced back by the system's dynamics? If the system can change its constraints autonomously, it could create new ones too. If that happens, we have a model of autonomy and dynamically emergent goals. We argue that *intrinsic* and dynamically emergent constraints are necessary (but insufficient) to have a realistic model of human psychology. However, as it is currently formulated, Active Inference and Bayesian Mechanics cannot accommodate such dynamicity and intrinsic constraints.

To answer why this is so, we need to trace back to the fundamental assumption of BM - that every existing system is a form of stochastic dynamical system with characteristic states/paths. On top of that, we also need to introduce some terminology of dynamical systems theory and Aristotelian causes from Koutroufinis (2017) and Rosen (1985). Every dynamical system comprises two kinds of causal factors - *intrinsic* and *extrinsic*. Intrinsic factors are those the system's dynamics can influence, while extrinsic factors are fixed and cannot be influenced.

Going back to Eq 1, our intrinsic factors are the state variables (x; when partitioned μ, s, a, η); extrinsic factors are the independent variables and parameters. However, these are only first-order factors. The second-order extrinsic factors are those that operate on the first-order factors, in our case, the deterministic flow f. To introduce Aristotelian causes, we turn to a mathematically equivalent way of writing Eq 1,

$$x(t) = \int_{t_0}^{t} f(x_\tau)\,d\tau + C(x(t_0)) \qquad (2)$$

where, initial state $x(t_0)$ is the material cause, and operator $\int_{t_0}^{t} f(x_\tau)\,d\tau$ is the efficient cause of the effect $x(t)$ (Rosen, 1985). Given these terminologies, we will return to Koutroufinis (2017).

In all dynamical systems, Koutroufinis (2017) argues that second-order operators/efficient causation have to be *extrinsic* - in the sense of not being influenced by the system's dynamics. The necessary reason is that dynamical systems theory falls under the 'logic of machines,' i.e., the logic of state-determined systems with no *intrinsic* constraints and *internally related* efficient causation. As we will see later, this necessity is a direct outgrowth of classical physics' substance ontology and its accompanying view of efficient causation as an external force acting on an inertial matter that is epistemologically inherited in state-determined systems.

Moreover, this extrinsic nature between the dynamics and second-order function prevents any new generation of intrinsic factors at the first-order level. These two essential properties of dynamical systems are argued to be incompatible with empirical, biological facts of living systems (Koutroufinis, 2017). For example, during their growth (and other activities), cellular organisms synthesize a vast array of proteins resulting in novel functions (second-order factors) and relations between first-order factors. Also, these new relations produce varying types of molecules (first-order factors) that were not already present.

The extrinsic nature of the 'ontological constraint' and its inability to generate new first-order intrinsic factors make the underlying state variables fixed without any change or growth. Thus, while Active Inference can model the apparent change in position *within* a state-space, it cannot model the real change *of* the state-space itself, as observed in biological and cognitive systems. This fixed state space is what leads to

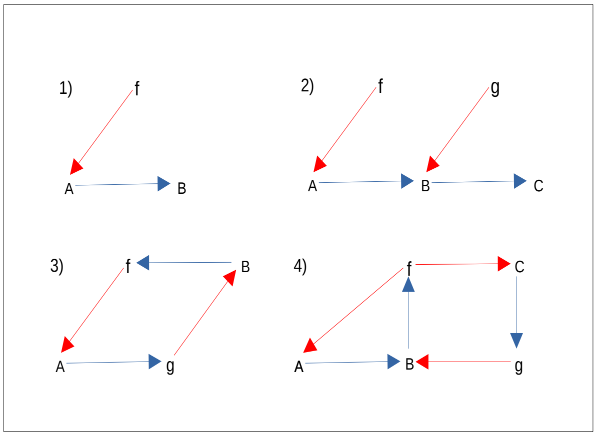

Figure 2: Rosen's category theoretic mappings depicting Simple (1 & 2) and Complex Systems (3 & 4). Red and Blue arrows indicate Aristotle's efficient and material causes, respectively. All simple state-determined systems are Turing computable, owing to their 'logic of machines' that always have extrinsic higher-order factors.

closed generative models.

However[3], one could postulate a higher-level function space (like evolution) that could make the state-space and generative models change dynamically. Nevertheless, the question becomes whether that higher-level space is fixed or changing. If the latter, we get into an infinite regress (by positing an even higher-level space); if the former, we are back to a closed ontology. The rejection of such postulations could be summarized as,

> 'Both [Whitehead and Peirce] reject physical necessity, and both philosophers were aware that the challenge of defending such a [process] realism is to find a way to model change such that natural laws themselves change' (Auxier & Herstein, 2019).

Thus, modeling change without getting into an infinite regress, nor positing an unchanging, privileged level, is precisely what a process ontology yields and is what we argue to be impossible in substance ontological state-determined models.

Substance and External Relations

As stated earlier, all models of dynamical systems fall under the 'logic of machines' category - to the extent that they cannot model *intrinsic* constraints. At the same time, as long as BM assumes that it completely explains life and mind purely in terms of dynamical systems theory, it presupposes a mechanistic ontology. To put it in Koutroufinis (2017)'s words:

> 'an ontology can be described as a 'mechanistic systems ontology' or simply a 'mechanistic ontology' if it implicitly or explicitly assumes that the term 'system' refers to real entities the inner causality of which can, in principle, be explained by models obeying the logic of the Turing or non-trivial machine.'

The key term here is *inner causality* and its nature in mechanisms. Before investigating causality, we need to explicate the link between mechanistic and substance ontology. Classical mechanics and its variants borrow from substance metaphysics the assumption of physical/material *substance* as ontologically primary[4]. This assumption, in turn, leads to the view of nature as 'all the things that exist are physical things—either basic bits of matter or made up of bits of matter' (Campbell, 2009).

Crucially, such particles/substances 'are supposed to exist independently of anything else: there are no relations *intrinsic* to [it]' (Bickhard, 2019) and are fundamentally unchanging. Given this nature of substances, the only relation predicable of them is *external relations*.[5] On top of these immutable particles, Newton posited external forces which cause changes to its position in space through accelerations.

The mathematical image of such a substance-mechanistic ontology was the R^3 space occupied by an unchanging particle with its instantaneous position (state variable) determined by dynamical laws independent of it and its motion. While significant developments were made from this particle mechanics, Rosen (1985) argues that explicit separation of dynamical laws and system dynamics were still the epistemological presupposition of state-determined models like analytical, statistical, and quantum mechanics.

Thus, at the root of *extrinsic* efficient causes in all state-determined systems is the substance ontological assumption of externally related matter with external forces as the efficient cause of position change. Given this background, it is clear why in mechanisms, 'efficient causes have to be extrinsic' (see above and Fig 2.1-2.2). Owing to their substance metaphysical presupposition, any form of mechanics (including Bayesian Mechanics) has to follow a logic of causality that necessarily grounds in an extrinsic factor, which makes it impossible to model our intrinsic constraints - a form of *impredicative* causality.

In the next section, we will look at an alternative to substance metaphysics, which takes relations, change, and activity seriously. This, in turn, yields powerful resources to model biological and cognitive agents.

Process and Internal Relations

Unlike substance metaphysics, process metaphysics views *processes* as fundamental and 'matter or bits of matter' as organized actualization of processes. This shifts our view of

[3] We thank one of our reviewers for pointing this out.

[4] There are other critical assumptions like the elimination of potentiality, absolute space, and time which we will not get into here.

[5] For a definition and concrete example of internal, external relation, and impredicativity, see next section.

nature to ‘all things have to be conceived fundamentally as *processes* of various scales and complexity, having causal efficacy in themselves’ (Campbell, 2009).

Thus, if the default condition for substance metaphysics was inertness and isolation, then it is the opposite - activity and relations for process metaphysics. Crucially, self-determining activity and internal relations, capable of handling *intrinsic* constraints and *internally related* efficient causes. We are now in the correct position to elaborate on internal and external relations.

In logic, two terms are internally related if one or both the term’s *existence* depends on having that relation between them (Campbell, 2011). In other words, it is an essential relation for the constitution of the term/s. Externally-related terms do not have constitutive or essential relations between them. Let us visit some examples.

A classic instance of internal relation is the relation between the arc of a circle and its center (Bickhard, 2003). An arc cannot *exist* as ‘that’ arc without its relation to the center. Another crucial example is Robert Rosen’s impredicative cycle (Fig 2.3). Note that the efficient causes f and g mutually cause each other in an impredicative cycle. Without f, g would not exist, and without g, f would not exist - A form of internally related efficient causation.[6] Thus, the very existence and constitution of the term/s depend on such relations.

Contrast this with the external relation between ‘...’ of Morse code and its content ‘S.’ There is nothing *intrinsic* in ‘...’ that depends on ‘S.’ ‘...’ could exist perfectly fine as ‘...’[7] without that Morse code relation. In fact, all such informational encodings are external relations (Bickhard, 2003). While substance metaphysics can only offer external relations, both internal and external relations play a crucial role in process metaphysics.[8]

The purpose of these elaborations is to emphasize that in ‘a process metaphysics there are no particulars’ (Seibt, 2010), i.e., there are no inert, externally-related substances but rather internally organized actualization of processes. Within this framework, there is a continual mutual influence (both internal and external) among processes, with those influences embodying causal powers.

Furthermore, because of the relational character of processes, their causal powers too are relational. Also, since at least some of these relations are internal, *constitutive change* and thus *emergence/emergent causality* is legitimate in process metaphysics. Thus, process metaphysics provides powerful resources to model both external & predicative forms of causality and impredicative forms.

To sum up, the two essential aspects of process metaphysics are activity (with its inherent causal power) and relations (including internal relations). Combining these two aspects, one could heuristically think of a process as an organization of causes, with novel organizations yielding emergent processes. These aspects of process metaphysics are what Rosen’s Relational Biology is about.

While explaining the details of Rosen’s brilliant insights is beyond the scope of this paper, we would merely like to highlight two classes of systems that he identified - simple and complex systems (Fig 2). Simple systems exhibit only predicative forms of causality, while complex systems can exhibit both predicative and impredicative forms.

The critical difference between these systems is the extrinsic and intrinsic higher-order causal factors (efficient causes f and g). In Rosen’s complex systems, the system’s activity influences (in fact produces) the higher-order factors, while in simple systems, the highest level is always extrinsic. Thus, by adopting process-relational metaphysics, we are endowed with a powerful logic to scientifically model the complexity of biological and cognitive systems.

Conclusion

We started our study with the goal of analyzing the implicit metaphysical assumptions present in Cognitive Science’s core theories - Active Inference and Bayesian Mechanics (BM). Furthermore, we focused on the goal-oriented aspects of human psychology and its dynamic properties to cast light upon those metaphysical commitments. Through this analysis, we find that Active Inference is based on substance metaphysics, preventing it from capturing the novelty and growth of goals associated with biological and cognitive systems.

Specifically, the closed nature of generative models used to explain human cognition is derived from the ‘ontological constraints’ of BM’s ‘things.’ The fixed nature of these ‘ontological constraints’ was traced back to the ‘logic of machines’ and its extrinsic higher-order factors. Furthermore, we found that this logic was a natural outgrowth of substance metaphysical assumptions and its apparent incompatibility with internal relations and impredicative causality.

We also describe some key features of process metaphysics and the powerful resources it yields to model predicative *and* impredicative process organizations. We end with a brief outline of Rosen’s Relational modeling as a suitable framework for biological and cognitive systems. Recent advances in Active Inference toward a more relational, category-theoretic approach are encouraging (Smithe, 2022). However, category theory in and of itself is not a silver bullet for conceptual and theoretical problems. It remains to be seen whether the recent formulations avoid the pitfalls of substance metaphysics described here.

Acknowledgments

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[6]Rosen calls this closure to efficient causation.

[7]For example, it could be used perfectly well inside a python function, without meaning ‘S’ wherever it is used.

[8]We are skipping technical complications in process philosophy like past being externally related to present and present being internally related to past due to space constraints.

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